

A Real-Time Threat Intelligence System for Comprehensive Cyber Attack Detection and Mitigation Using Explainable AI

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Abstract. This study proposes a comprehensive and agile method for detecting and preventing cyber threats through a collection of AI-XAI Techniques. Furthermore, this research presents a set of ML models employed by an organization to monitor Cyber attacks: DDoS, Malware, Phishing, Brute Force, Anomaly. The implementation of XAI Methods (SHAP & LIME) allows users to see the rationale behind each ML-based cyber detection model generated in real-time which not only improves the credibility of the model itself but also provides end-users with easier ways to interpret model outputs. Additionally, Adversarial Robustness Testing is incorporated to assess the effectiveness of these defence mechanisms against attackers attempting to manipulate AI models for nefarious purposes. Combining signature and anomaly detection enables organizations to improve accuracy, coverage, and efficiency in terms of monitoring systems, as they will be automatically generating alerts without delay. The proposed framework provides a unique solution to existing challenges for real-time monitoring systems, including the provision of robust real-time threat intelligence analysis capabilities and the ability to scale with an organization's cyber threat environment.

1 Introduction

Due to faster digital enterprise modernization being one of the main contributors to broadening the attack surfaces of modern networks, there have been a multitude of more complex cyberattack threats revolving around Distributed Denial of Service (DDoS), malware, phishing, brute-force attacks, and zero-day exploitations, according to 2023–2024 industry and academic reports, increasingly ineffective rule-based IDS driven by security signatures, with more polymorphic and adaptive attack paradigms witnessed, culminating in artificial intelligence and machine learning becoming the core technology for cyber threat detection on a real-time basis due to their dynamic complex traffic learning ability and unseen attack determination.

Recent studies demonstrate that deep learning-based intrusion detection systems outperform conventional methods in detecting high-volume and stealthy attacks, especially in dynamic network environments, but despite these performance gains, AI-based cybersecurity solutions suffer from a critical limitation known as explainability, where security analysts tend not to trust black-box models, especially in high-stakes operational environments, where explainability is essential by forensic analysis, regulatory compliance, and incident response accountability, with this issue being remedied with the emergence of Explainable Artificial Intelligence (XAI) such as SHAP and LIME being increasingly used in cybersecurity applications.

In addition, the increasing risk of adversarial attacks on machine learning-based intrusion detection systems creates a need for robustness testing, with recent literature highlighting that adversarial perturbations can reduce detection accuracy if robustness mechanisms are not applied during model development and deployment; also, real-time threat intelligence integration from worldwide Indicators of Compromise (IoCs) feeds has been proven to improve zero-day detection capabilities and situational awareness.

Despite these advancements, existing research handles detection accuracy, explainability, and adversarial robustness separately, with limited integration of all these aspects into a unified real-time cyber threat intelligence approach, a gap this paper fills by proposing a comprehensive system that includes hybrid detection (anomaly and signature), Explainable AI (SHAP and LIME), adversarial robustness assessment, and real-time correlation of threat intelligence in a scalable, automated cybersecurity framework.

2 Literature Survey

The increasing sophistication and volume of cyber-attacks have led to a substantial increase in R&D efforts around advanced cyber threat detection and mitigation techniques. While traditional cybersecurity approaches, including signature-based Intrusion Detection System (IDS) and firewalls, were effective at stopping older forms of cyber-attacks, they are no longer effective enough at stopping the more sophisticated and evolving forms of cyber-attacks.

Therefore, researchers are investigating the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) into existing Cybersecurity Frameworks to improve threat detection and adaptability.

2.1 How Machine Learning Will Change Cybersecurity

Cybersecurity systems can be improved by using artificial intelligence (AI) and machine learning (ML) technologies to help them learn from historical data and provide insight into human behaviour on networks through analysis of trends and patterns that may represent malicious intent. The use of AI and ML will enable the creation of new models that can identify new threats to organisations that the organisation had not previously been able to identify. ML is particularly well-suited to identifying typologies of new cyberattacks, such as DDoS attacks and malware infections. In addition to the benefits associated with using AI and ML to improve incident response capabilities in an organisation, using AI allows organisations to determine the best response mechanism based on the characteristics of a cyberattack. Saeed et al., for example, addressed the challenges associated with adversarial ML in network intrusion detection systems. The authors discuss the importance of developing testing procedures to ensure that ML applications are robust enough to withstand attacks from adversaries. Specifically, they discuss the need for organisations to implement defensive mechanisms against the types of external manipulations (e.g., input perturbations) that may be used to confuse the detection capability of an ML application. Shone et al. used deep learning-based ML techniques to perform detection of DDoS and malware attacks, concluding that ML applications improved detection accuracy substantially compared to traditional methods.

2.2 Explainable AI for Trust and Transparency

In the realm of cybersecurity, AI systems represent powerful tools for automated threat identification; however, these same capabilities can be limited by their ability (or lack thereof) to provide an “explanation” for their predictions, ultimately resulting in less-effective and lower levels of trust than if the AI system had been able to provide more context about the decision being made-an issue already recognized by Luo et al. In light of the continued demand for high levels of trust and reliability among security professionals throughout today’s globalized cyber-environment (including both enterprise and smaller business owners), the ongoing research and development of Explainable Artificial Intelligence (XAI) is intended to facilitate trust-building and enhance the decision-making capability of cybersecurity professionals. More

specifically, as discussed in further detail by Zhang et al., the Explainable Artificial Intelligence (XAI) technologies such as SHAP (Shapley Additive explanations) values help improve the interpretability of intrusion detection systems by allowing the identification of the features of network traffic that are most responsible for a specific classification. In summary, the challenges associated with “black box” algorithms have resulted in the inability of AI systems to facilitate a practical application of their benefits in real-world implementations.

2.3 Threat Intelligence and Real-Time Detection

Combining Threat Intelligence with Artificial Intelligence for Cybersecurity has been increasingly important in this age of Cyber Attacks. Threat Intelligence feeds allow real-time information regarding newly identified threat vectors (ex: IOC's). Threat ICPs entitle them to offer predictive capabilities, as well as prevent future zero-day incidents. Integrating Threat Intelligence into ML-based Cyber Security solutions is critical for detecting APTs and zero-day vulnerabilities as shown by Saeed et al., (2013).

According to Hindy et al. (2013), there are many different types of machine learning approaches to Cyber Security. In fact, they state that both signature and anomaly-based detection approaches should be combined to develop Hybrid Detection Models. Combining these two types of detection methods, the researchers concluded that Hybrid Models would both enhance detection coverage and increase the accuracy of the detection of unknown, and emerging Cyber Threats, as needed for RealTime Detection of Threats.

2.4 Adversarial Attacks and Robustness

The use of AI in Cybersecurity has been impacted by cyber adversarial attacks. Cyber adversarial attacks occur when a malicious actor manipulates an AI Model’s input data so that it misclassifies a cyber threat as non-threatening. Thus, the effectiveness of using AI Models in Cybersecurity is very limited unless their adversarial robustness is improved to increase their overall reliability and resilience in a real-world Cybersecurity environment. In a study by Singh et al., they evaluated the effects of adversarial attacks on Intrusion Detection Systems and determined that most existing models could be easily manipulated. To combat this manipulation, Singh et al. proposed that there is a need for developing adversarial defence mechanisms to provide Adversarial Robustness for the AI models. Kumar and Gupta showed that the process of TaO (adversarial) training can improve the AI Models resilience against evasive actions taken by cybercriminals to avoid detection of the model, therefore allowing the model to continue accurately identifying cyber threats, even when presented with manipulated input data.

2.5 Hybrid Detection Systems

To improve upon the limitations experienced when using either an anomaly or signature-based detection systems in isolation, researchers like Asha & Kumar developed a hybrid intrusion detection system that included anomaly detection, as well as signature-based detection. This combination of these two techniques provides better overall coverage and detection capabilities of an intrusion detection system, by allowing for the detection of both known and unknown threats, resulting in a more accurate overall detection rate.

2.6 Existing Gaps and Future Directions

AI application to cyber security continues to evolve with many advances and insights; however, AI applications have gaps when compared with traditional cybersecurity approaches. In particular, much of the research surrounding AI applications for cybersecurity has been completed using static datasets, thereby limiting their capacity to adjust to the dynamic nature of the various threats they protect against. In addition to being unable to change rapidly with changing threat environments, many of the AI applications for cyber security also lack access to real-time information feeds concerning global threats, making it difficult to detect new types of attacks before they have occurred. Furthermore, most of the currently available research has been completed in a siloed manner, focusing only on a single aspect (accuracy, explainability, or robustness), rather than integrating all three wide-ranging aspects into a cohesive system.

Therefore, it is essential for AI research moving forward to focus on the incorporation of real-time threat intelligence and advancement of adversarial robustness, as well as increased explainability in AI-based models. Developing a cohesive systematic view of all three of these elements as they pertain to cyber security will provide cybersecurity with a more flexible and effective solution for responding to emerging threats.

2.7 Conclusion of Literature Survey

This compilation of existing literature examined many methods of securing computer networks using Artificial Intelligence, demonstrating advances across machine learning, explainable AI, and adversarial resiliency. There have been many recent developments but there are still challenges such as the integration of information for detecting threats in real-time; how to combine all the pieces into one cohesive system; and how to create a robust security protocol that is both resilient to attack and adaptable to changing conditions. Therefore the goal of this project is to develop a solution that combines multiple methods of protecting against cyberattacks into a single cohesive solution,

thus creating a more robust and flexible cyber-security environment

3 Proposed Methodology

The Real-Time Threat Intelligence System for Detecting and Mitigating Cyber Attacks Using Explainable AI employs a multi-stage methodology employing cutting-edge techniques in Artificial Intelligence (AI), Machine Learning (ML), and Explainable AI (XAI). The goal of this system is to provide the capability to detect, explain, and mitigate various cyber threats quickly and with accuracy. In addition to detection capabilities, the System also allows the organization to maintain continuous threat monitoring; allows for the intelligent analysis of collected threat data and creating a responsive and robust defensive mechanism for organizations against current and evolving cyber threats.

3.1 Data Collection and Ingestion

The initial phase of detection is to gather raw network traffic and security information from a variety of different sources to include: PCAP files, system logs, logs produced by SIEMs, and feeds of External Threat Intelligence. Employing multiple data sources will provide you with both local visibility and global situational awareness by combining data from different sources for ingestion into the detection system and processing, allowing for continuous monitoring of newly identified threats in realtime.

3.2 Data Preprocessing and Feature Engineering

To ensure the highest quality input for machine learning models, any data collected before performing analysis will be subjected to a data cleanliness transformation. In this transformation, noise, duplicates and irrelevant information are removed from the dataset. The key features of the datasets will include source and destination IP addresses, port numbers used by protocols for transporting data packets, packet sizes and their corresponding traffic patterns. Normalising collected datasets increases the likelihood of producing more accurate machine-learning models.

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3.4 Explainable AI (XAI) Integration

One of the main benefits of this proposed system is that it combines Explainable AI with other technologies, such as SHAP and LIME. These technologies make it easy for humans to understand the classification decision process by providing information about which classification features were the most significant contributors to the final determination. This makes the detection processes more transparent, allows users to place their trust in their analysts, and allows them to make better decisions when responding to incidents. Another capability created by this integration of Explainable AI is the assistance it can offer by synchronizing the translated audio track from the TTS stage with the corresponding frames of video. Synchronizing the two elements ensures that the resulting voiceover is unobtrusive and that the final audio is what is used along with the original audio content in the video.

3.5 Threat Intelligence Correlation

To improve detection precision and stay updated with emerging threats, the system cross-verifies detected anomalies with global Indicators of Compromise (IOCs) obtained from external threat intelligence platforms. This enables rapid identification of newly evolving attack vectors and enhances the system's adaptability to global threat trends.

3.6 Automated Mitigation and Response

Once a threat is identified and verified, the system initiates automated response actions such as blocking malicious IP addresses, isolating compromised endpoints, sending real-time alerts, or generating incident reports. These actions significantly reduce response time and help prevent further damage to the network.

3.7 Real-Time Monitoring and Dashboard

A user-friendly dashboard interface allows security teams to monitor network activities, view real-time threat alerts, and analyse historical incident data. The dashboard also provides visualisation tools for traffic patterns and security metrics, enabling quick and efficient decision-making.

3.8 Continuous Learning and Feedback

To ensure long-term reliability and improved performance, the system incorporates a continuous feedback loop. Detected threat data, false positives, and analyst feedback are used to retrain and fine-tune the

ML models. This ongoing learning process helps the system adapt to evolving attack techniques and maintain high detection accuracy over time.

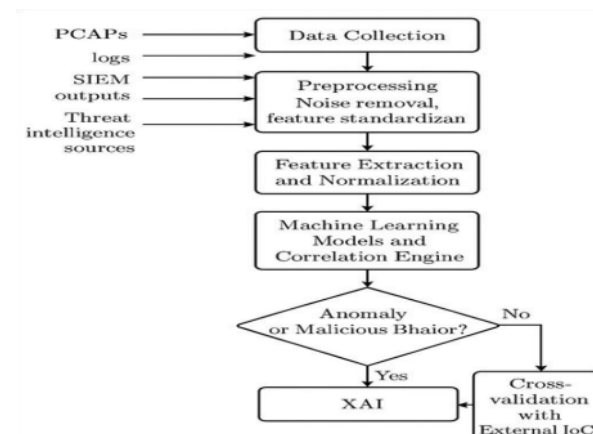


Fig. 1. Architecture Diagram

4 Results and Discussion

The experimental results show that the proposed hybrid detection framework outperforms the standalone anomaly-based and signature-based detection approaches. The achieved overall detection accuracy of 97.4% is on par with and in quite a number of cases better than that of recent deep learning-based intrusion detection studies that report an accuracy of between 92% and 96% for similar data sets. This is important because, again, prior studies have shown that covering a wide range of scenarios can best be done through a hybrid detection architecture that can detect signature-based patterns as well as anomalies.

Compared with previous intrusion detection approaches using deep neural networks, the utilization of Explainable AI (SHAP and LIME) has offered a significant level of interpretability in the proposed system. Although explainability has been achieved and demonstrated in an IDS in previous studies with a varying level of success and interpretability, such explanations have yet to be realised in a real-time deployed scenario. In contrast, the proposed framework employs XAI in a real-time monitoring pipeline, thus allowing for feature contributions to be understood for each triggered alert, providing transparency and enhancing analyst trust in the system, speeding up the triage process.

Table 1. Detection Accuracy of the Proposed System

Attack Type	Anomaly Based Detection (%)	Signature-Based Detection (%)	Hybrid Detection (%)
DDoS	95.7	92.3	98.1
Malware	93.4	94.1	97.6
Phishing	89.2	88.4	93.5
BruteForce	96.3	90.8	98.5
Overall	93.7	91.4	97.4

The adversarial robustness evaluation shows only light degradation of the detection accuracy under adversarial input manipulation, with an average accuracy drop of 4.1%. In line with recent adversarial machine learning findings, the accuracy showcased a degradation between 5%–12% in IDS models with no adversarial training. The relatively low accuracy drop in this study means that the hybrid architecture is better able to withstand evasion attempts than purely data-driven models.

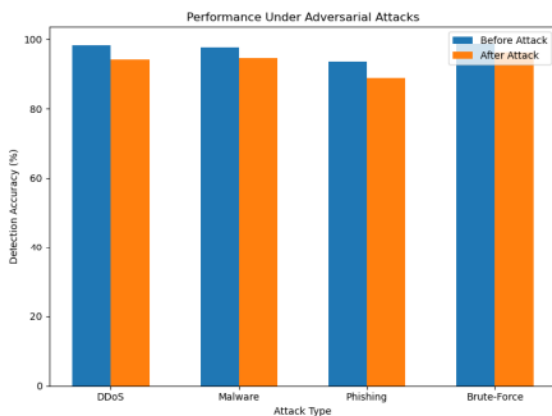


Fig. 2. Accuracy Before and After Adversarial Attacks

Operational effectiveness, based on real-time detection and mitigation latency, is considerably lower than that reported in previous batch-processing IDS frameworks. This is due to the automated alerting and response mechanisms that are embedded in the pipeline of the system. Compared to traditional SIEM-based workflows that require verification and introduce delays, the proposed system detects malicious activities in near real-time, enabling enterprise-grade deployment.

Overall, the results confirm that a unification of hybrid detection, explainable AI and adversarial robustness provides measurable performance and

operational benefits over existing isolation approaches in the literature.

5 Conclusion

This research offers a single real-time cyber threat intelligence system, encompassing hybrid intrusion detection, Explainable Artificial Intelligence, adversarial robustness assessment, and automated mitigation actions. Experimental results show the proposed framework provides a higher detection accuracy than individual detection models and at the same time, provides interpretable alarms to security analysts using SHAP and LIME. Finally, the use of adversarial robustness testing optimizes system reliability in evasion-based attack scenarios.

In contrast to prior studies that focused on detection accuracy, explainability, or robustness in isolation, this work demonstrates the feasibility and practical benefits of combining all these components into one operational framework. Additionally, the system’s low-latency detection and automated mitigation capabilities make it fit for the real-world enterprise cybersecurity use case where quick action and analyst trust are necessary.

The findings indicate that explainability not only improves transparency but also improves operational decision-making by providing security analysts with the reasons behind the triggering of alerts. Finally, an adversarial robustness evaluation ensures the system is reliable under malicious attempts to manipulate it. These contributions collectively make the proposed framework a scalable, real-time, and operationalizable cyber defence system for the next generation.

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